INCREMENTAL LEARNING METHOD AND SYSTEM FOR DEFECT IMAGES UNDER DRONE CLOUD-EDGE COLLABORATION

TECHNICAL FIELD

The present application relates to the technical field of incremental learning and annotation for defect images, and particularly to an incremental learning method and system for defect images under drone cloud-edge collaboration.

BACKGROUND ART

With the development of drone technology, using drones to replace manual inspection of transmission corridors has become increasingly common. Currently, during transmission line inspection by drones, the mainstream approach involves sending images and video data captured by the equipment to an artificial intelligence platform, which then calls upon its models for transmission fault detection and defect identification. However, this approach faces the following issues: 1. The AI platform models are static and do not currently support self-learning iteration to improve defect identification capabilities. 2. Excessive pressure on cloud computing and channel networks; current cloud computing in AI platforms cannot meet the requirements of application services with high demands for real-time performance and security, such as wildfire detection in defect inspection which requires high real-time performance, a requirement currently unmet by existing cloud AI platforms.

Therefore, designing an efficient data annotation and model update mechanism for timely and accurate inspection and defect detection of transmission lines is an important means and urgent task to ensure the safe and stable operation of the power grid.

SUMMARY OF THE INVENTION

In view of this, it is necessary to provide an incremental learning method for defect images under drone cloud-edge collaboration. This method utilizes edge computing nodes to achieve real-time defect detection and leverages the powerful computing capabilities of the cloud for incremental model updates. While ensuring real-time detection, it can effectively adapt to newly emerging defect types, significantly improves the accuracy of defect identification and system adaptability, is easy to promote and apply, relatively simple to operate, and suitable for promotion in more scenarios.

The present invention proposes an incremental learning method and system for defect images under drone cloud-edge collaboration. This is achieved by constructing a distributed cloud-edge collaborative transmission line defect identification platform, deploying an inference and semi-automatic annotation system on the edge side, and establishing a multi-model incremental training system based on digital twin technology on the cloud side. Through cloud-edge collaborative incremental learning and combined with manual or assisted system sample annotation, the method continuously optimizes the models. When the accuracy of an incrementally trained model is significantly better than the original model, it is deployed to the edge side to update the original model. Meanwhile, a crowdsourcing pipeline mechanism is adopted to split the annotation task into multiple subtasks, integrating the advantages of multiple models to improve annotation efficiency and accuracy.

In a first aspect, an embodiment of the present application provides an incremental learning method for defect images under drone cloud-edge collaboration, comprising:

S1: Constructing a cloud-edge collaborative transmission line defect identification platform, deploying an inference and semi-automatic annotation system on the edge side, and establishing a multi-model incremental training system based on digital twin technology on the cloud side;

S2: Drones using LPWAN technology to collect line status data in real time and upload it to the edge side;

S3: The edge side invoking multiple pre-trained models, employing a crowdsourcing pipeline mechanism for pre-annotation, and summarizing low-confidence samples to send to the central cloud;

S4: The central cloud performing assisted annotation of samples manually or using Label Studio, and retraining the incremental models in the digital twin system;

S5: Calculating the accuracy of the models after incremental training and comparing it with the original models;

S6: If the accuracy improvement exceeds a set threshold, deploying the new models to the edge side to update the original models.

In an optional embodiment of the present invention, step S1 of constructing the distributed cloud-edge collaborative transmission line defect identification platform comprises deploying the inference and semi-automatic annotation system on the edge side and constructing the multi-model incremental training system based on digital twin technology on the cloud side:

The platform consists of a central cloud, an edge side, and drones. The edge side comprises field devices, edge gateways, and edge clouds, achieves node interconnection through a multi-level distributed architecture, and converts private communication protocols into the standardized OPC UA protocol to support heterogeneous device access and data collection, transmission, and processing, with computing tasks distributed to multiple nodes for parallel execution.

The inference and semi-automatic annotation system comprises: a data input module for receiving images; a model annotation module for invoking various pre-trained models for preliminary annotation; an RTMDet inference service module for optimizing annotation results; and an annotation output module for saving and outputting the final annotations.

The multi-model incremental training system comprises: a digital twin layer for generating mirrored model replicas; a model management layer responsible for version control, performance monitoring, and dependency management; and an incremental training engine for adaptively adjusting learning rates based on online learning algorithms and a distributed framework.

Optionally, in one implementation of the present invention, S3 comprises: On the edge side, invoking multiple pre-trained models through the inference and semi-automatic annotation system, employing a crowdsourcing approach to distribute data and perform pre-annotation, summarizing low-confidence samples and sending them to the central cloud;

The multiple pre-trained models comprise a CNN model, an improved dual Unet model, and a Logits distillation model; a pipeline task mechanism is adopted, splitting the annotation task into multiple subtasks, forming candidate model combinations through permutation and combination of pre-trained models to execute the tasks, selecting the optimal combination based on confidence, and summarizing its low-confidence samples to send to the central cloud.

Optionally, S4 comprises: Collecting a transmission line defect image dataset and dividing it; performing resizing and normalization preprocessing on the images, with the edge side performing preliminary screening and compression; loading pre-trained models via MMDetection for preliminary annotation, manually correcting the results, and saving them; using the annotated data to retrain the incremental models in the digital twin system.

Optionally, the improved dual Unet adopts an asymmetric structure, comprising UNet1 and UNet2, where the two encoders extract low-level and deep-level features respectively, perform feature interaction and fusion at the decoder layer, and output predictions, using a joint loss function composed of cross-entropy loss and Dice loss, the formula is:

$$L_{ce} = -\sum_{i=1}^{N} p(x_i)\log(q(x_i));$$

Wherein, $p(x_i)$ represents a true distribution of sample x_i, $q(x_i)$ represents a predicted distribution of sample x_i, N represents a number of samples;

$$L_{dice} = 1 - \sum_{k}^{K} \frac{2w_k \sum_i^N p_{k,i} g_{k,i}}{\sum_i^N p_{k,i}^2 + \sum_i^N g_{k,i}^2};$$

Wherein, $p_{k,i}$、$g_{k,i}$ respectively represent a predicted probability value and a true label value for class k and K are numbers of samples and classes, w_k represents a weight for the class k;

$$L_{total1} = L_{ce} + L_{dice};$$

Wherein, the Logits distillation model consists of three parallel networks: a standard teacher network adopting a UNet structure with embedded attention, a student network using a lightweight UNet, and an adversarial teacher network adopting a U-CliqueNet structure with Clique Blocks replacing convolutional layers. The model uses a joint loss function consisting of hard and soft losses, wherein, the hard loss function is:

$$L_{hard} = -\sum_{i=1}^{N} p(x_i)\log(q(x_i));$$

Wherein, $p(x_i)$ represents the true distribution of sample x_i, $q(x_i)$ represents a predicted distribution of the student network model for the sample x_i, N represents the number of samples;

The soft loss function is L_{soft}:

$$L_{soft} = T^2 KL(q_{teacher1} \| q_{student} \| q_{teacher2});$$

Wherein, T represents a temperature parameter, $q_{teacher1}$、$q_{student}$、$q_{teacher2}$ respectively represent probability distributions after high-temperature softening of the standard teacher network model, the student network model, and the adversarial teacher network model;

the total loss function is L_{total2}:

$$L_{total2} = \alpha \cdot L_{hard} + (1-\alpha) \cdot L_{soft};$$

Wherein, α represents a hyperparameter for adjusting weights of the hard loss and the soft loss, $\alpha \in [0,1]$.

Optionally, in one implementation of the first aspect of the present invention, the step of calculating accuracy of each incrementally trained model and comparing it with accuracy of the original model, comprises:

Evaluating accuracy of each model through a mean Intersection over Union, formula being:

$$mIoU = \frac{1}{N+1} \cdot \sum_{i=0}^{N} \frac{c_{ii}}{\sum_{j=1}^{N} c_{ij} + \sum_{j=1}^{N} c_{ji} - c_{ii}},$$

Wherein, N represents a total number of classes, c_{ii} represents a number of samples where the true class is i and the predicted class is also i, c_{ij} represents a number of samples where the true class is i and the predicted class is j.

An incremental learning system for defect images under drone cloud-edge collaboration comprises:

A cloud-edge collaborative platform construction module: for constructing the cloud-edge collaborative platform, deploying the inference and semi-automatic annotation system on the edge side, and establishing the multi-model incremental training system based on digital twin technology on the cloud side;

A data collection module: for collecting line status data in real time using drones and LPWAN technology and uploading it to the edge side;

A first annotation module: for the edge side to perform pre-annotation using a multi-model crowdsourcing pipeline mechanism, and summarize low-confidence samples to send to the central cloud;

A second annotation module: for the central cloud to perform assisted annotation manually or using Label Studio and retrain the incremental models;

An accuracy calculation module: for calculating the accuracy of the incremental models and comparing it with the original models;

A model update module: for deploying the new models to the edge side to update the original models when the accuracy improvement exceeds a threshold.

In a third aspect, an electronic device is provided, comprising a processor and a memory, wherein the processor, when executing a program stored in the memory, implements the method according to the first aspect.

In a fourth aspect, a computer-readable storage medium is provided, storing a program which, when executed, implements the method according to the first aspect.

The present invention provides an incremental learning solution for defect images under drone cloud-edge collaboration, achieving transmission line defect identification by constructing a cloud-edge collaborative platform. The system deploys an inference and semi-automatic annotation system on the edge side and establishes a multi-model incremental training system based on digital twin technology on the cloud side. Drones collect line status data using LPWAN technology and upload it to the edge side. The edge side employs a multi-model crowdsourcing pipeline mechanism for pre-annotation and sends low-confidence samples to the central cloud. After completing assisted annotation, the central cloud retrains the incremental models, and deploys them to the edge side to update the original models when the model accuracy improvement exceeds a threshold.

The core of this solution comprises two parts: a cloud-edge collaborative incremental training mechanism, which continuously optimizes model accuracy to improve performance; and edge-side inference and semi-automatic annotation technology, which splits tasks via a crowdsourcing pipeline, integrating the advantages of multiple models to balance annotation efficiency and accuracy.

Beneficial Effects:

1) Through the cloud-edge collaborative incremental learning mechanism, low-confidence samples are automatically screened, and manual assisted annotation and model retraining are performed in the cloud, effectively improving model identification accuracy and enabling rapid deployment and update at the edge side after significant model performance improvement.

2) Combining edge-side model inference and semi-automatic annotation technology, efficient and precise sample annotation is achieved with the assistance of manual or system input.

3) Adopting a crowdsourcing pipeline task mechanism, the annotation task is split into multiple subtasks executed collaboratively by different model combinations, improving efficiency while integrating the advantages of multiple models to further enhance annotation accuracy.

4) The method is simple to operate, highly versatile, and has good prospects for promotion and application.

DESCRIPTION OF DRAWINGS

Figure 1 is a schematic flowchart of the incremental learning method for defect images under drone cloud-edge collaboration according to the present invention.

Figure 2 is a framework diagram of the distributed cloud-edge collaborative transmission line defect identification platform according to the present invention.

Figure 3 is a diagram of the multi-level distributed management architecture of each edge node according to the present invention.

Figure 4 is an architectural diagram of the dual Unet model structure according to the present invention.

Figure 5 is an architectural diagram of the Logits distillation model structure according to the present invention.

Figure 6 is a schematic diagram of the modules of the incremental learning system for defect images under drone cloud-edge collaboration according to the present invention.

Figure 7 is a schematic diagram of an electronic device provided by an embodiment of the present invention.

EMBODIMENTS

The technical solutions in the embodiments of the present application will be clearly and completely described below with reference to the accompanying drawings in the embodiments of the present application. It is apparent that the described embodiments are only a part of the embodiments of the present application, and not all of them.

Embodiment 1

Figure 1 is a schematic flowchart of an incremental learning method for defect images under drone cloud-edge collaboration according to an embodiment of the present application.

As shown in Figure 1, an incremental learning method for defect images under drone cloud-edge collaboration comprises:

S1: Constructing a distributed cloud-edge collaborative transmission line defect identification platform, deploying an inference and semi-automatic annotation system on an edge side, and establishing a multi-model incremental training system based on digital twin technology on a cloud side.

As shown in Figure 2, the platform consists of a central cloud, the edge side, and drones. The edge side comprises field devices, edge gateways, and edge clouds. The system is based on a multi-level distributed architecture. By converting private protocols into the standardized OPC UA protocol, interconnection of edge nodes and access of heterogeneous devices are achieved. Tasks are distributed to multiple nodes for parallel processing, completing data collection, transmission, and processing.

The inference and semi-automatic annotation system comprises a data input module, a model annotation module, an RTMDet inference service module, and an annotation output module. These modules are responsible for image reception, preliminary annotation using pre-trained models, result optimization and adjustment, and saving and outputting final results, respectively.

The multi-model incremental training system consists of a digital twin layer, a model management layer, and an incremental training engine. These components respectively implement model mirror generation, version and performance management, and adaptive learning rate adjustment based on online learning and a distributed framework.

S2: Utilizing drones employing low-power wide-area network technology to achieve real-time collection of line temperature, sag, and vibration state data, and uploading the collected data to the edge side.

In this embodiment, the drones employ LoRa-based LPWAN technology, which features long-range and low-power consumption, adapting to complex terrains and dynamic movement scenarios of drones. The drones are equipped with various sensors and use LPWAN to collect line status data in real time, supporting concurrent transmission from multiple nodes. Simultaneously, they function as mobile gateways to optimize coverage in blind spots and improve collection efficiency.

Data is uploaded to edge nodes via LPWAN. The edge side utilizes lightweight AI models to achieve fault feature extraction, sag analysis, and vibration assessment.

The cloud side is responsible for multi-model incremental training and big data processing. The edge side achieves real-time defect detection and assists in correcting low-confidence samples through an interactive interface. The cloud and edge sides communicate using MQTT/HTTP protocols. Edge nodes perform data filtering, while the cloud side focuses on model optimization.

S2 (Reiterated for clarity in flow): Drones employ LoRa-based LPWAN technology to collect line temperature, sag, and vibration data in real time and upload it to the edge side. LoRa features long-range and low-power consumption, adapts to complex terrains and mobile scenarios, and improves collection efficiency through concurrent transmission from multiple nodes.

After data is uploaded to edge nodes, lightweight AI models perform real-time fault feature extraction, sag analysis, and status assessment.

The cloud side deploys the multi-model incremental training system, responsible for model updates and big data processing. The edge side utilizes a lightweight engine to achieve real-time defect detection and assists in correcting low-confidence samples via an interactive interface. The cloud and edge sides communicate using MQTT/HTTP protocols. Edge nodes perform data filtering, while the cloud side focuses on model optimization.

As shown in Figure 4, the improved dual Unet model adopts an asymmetric structure, comprising UNet1 and UNet2. The two encoders extract low-level and deep-level semantic features respectively. After feature interaction and fusion at the decoder layer, prediction results are output. The model employs a joint loss function composed of cross-entropy loss and Dice loss.

Figure 5 is an architectural diagram of a Logits distillation model structure according to an embodiment of the present application.

As shown in Figure 5, the Logits distillation model consists of three parallel networks: a standard teacher network employing a UNet based on an attention mechanism, with attention modules embedded in its decoding part; a student network employing a lightweight UNet; and an adversarial teacher network employing a U-CliqueNet structure, using Clique Blocks to replace conventional convolutional layers. The loss function of this model consists of both hard loss and soft loss.

S4: In the central cloud, manually or using Label Studio to assist in annotating samples, and retraining the multiple incremental training models in the digital twin system based on the annotated data.

It comprises the following steps: collecting a transmission line defect image dataset and dividing it into a training set and a test set;

Performing preprocessing on the images, resizing and normalizing them according to the requirements of different pre-trained models. Simultaneously, performing preliminary screening and compression on the collected images at the edge side to reduce data transmission volume;

Selecting various pre-trained models and utilizing MMDETECTION interfaces to perform preliminary image annotation: loading model configurations and pre-trained weights, inputting preprocessed images for inference to generate preliminary annotation boxes; manually checking and adjusting the positions of annotation boxes to form corrected annotation results and saving them;

Using the annotated data to retrain the multiple incremental training models constructed based on digital twin technology.

S5: Calculating the accuracy of each incrementally trained model and comparing it with the accuracy of the original model.

It is understandable that, in this embodiment, the accuracy of each incrementally trained model is calculated and compared with the accuracy of the original model.

S6: If the comparison result is higher than a threshold, deploying the trained model to each edge node to update the original model.

Embodiment 2

A cloud-edge collaborative platform construction module 11: Constructing a distributed cloud-edge collaborative transmission line defect identification platform, deploying an inference and semi-automatic annotation system on the edge side, and constructing a multi-model incremental training system based on digital twin technology on the cloud side;

A data collection module 12: Utilizing drones equipped with LPWAN technology to collect line temperature, sag, and vibration data in real time and upload it to the edge side;

A first annotation module 13: On the edge side, invoking multiple pre-trained models, employing a crowdsourcing pipeline mechanism to perform pre-annotation on the data, summarizing low-confidence samples, packaging them, and sending them to the central cloud;

A second annotation module 14: In the central cloud, manually or using Label Studio to assist in annotating samples, and retraining the incremental models in the digital twin system based on the annotated data;

An accuracy calculation module 15: Calculating the accuracy of the models after incremental training and comparing it with the accuracy of the original models;

A model update module 16: If the comparison result is higher than a set threshold, deploying the trained models to the edge nodes to update the original models.

Figure 7 is an electronic device according to an embodiment of the present application. As shown in Figure 7, the electronic device comprises at least the following parts: a processor 101, a memory 100, a communication interface 103, and a bus 102.

In an embodiment of the present application, the memory 100 is configured to store instructions executable by the processor 101. The processor 101 is configured to, when executing the instructions, implement the modules of the device for incremental learning of defect images under drone cloud-edge collaboration as shown in Figure 6.

In an embodiment of the present application, a computer-readable storage medium comprises instructions which instruct a device to execute the method according to the first aspect. For example, the instructions instruct the device to execute the method shown by the flowchart steps in Figure 1.

Those of ordinary skill in the art should recognize that the above embodiments are merely used to illustrate the present application and are not intended to limit it. Any modifications and variations made to the above embodiments within the essential spirit and scope of the present application shall fall within the protection scope claimed by the present application.